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Cost Optimization of Blockchain Technology-enabled Supply Chain System using Evolutionary Computation Approaches: A Healthcare Case Study

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Abstract
This study aims to design a mathematical cost model for Blockchain Technology-enabled Supply Chain System (BT-enabled SCS), which may assist some companies that tend to evaluate the costs of BT as the main database in their SC system. We, therefore, identified the cost components of BT-enabled SCS based on the related literature review. The second purpose is to minimize the costs of the designed BT-enabled SCS model through Evolutionary Computation algorithms (CS/ACO/GA) as optimization techniques. To generate raw data for the model, the authors revised the Operations Research model and Inventory Management model as a mathematical formulation in Pharmaceutical Supply Chain. This mathematical formulation helps studies with a limitation of finding real data sets generate raw data in healthcare fields. Comparing CS/ACO/GA algorithms, the best solutions for the BT-enabled SCS cost model are CS and ACO with the higher Total Ranking Score (TRS) (scored by MSE, RMSE, and ROC), followed by GA standing in the second step. The more noteworthy finding is that all three algorithms have been able to find the global minimum for the BT-enabled SCS cost model with acceptable accuracy obtained from ROC.

Keywords: BT-enabled SCS, Cuckoo Search, Genetic Algorithm, Ant Colony Optimization, Blockchain Technology.

1. Introduction
Cost control is an important practice of identifying and reducing production expenses to increase business profits. Blockchain Technology-enabled Supply Chain System (BT-enabled SCS) promises to provide trustworthy transactions, better-managed operations, and traceability, but similar to other emerging technologies, the costs of BT-enabled SCS deployment are still largely undefined. BT-enabled SCS is the system using BT to improve the transparency, security, durability, and process integrity of SC. Azzi et al. (2019) consider that centralized SC systems expose SC to corruption, fraud, and tampering. Blockchain has been introduced in SC areas to make the chain more economic, reducing the total costs of the system. Implementing blockchain could improve efficiency in logistics and SCs since the technology accelerates the transfer of data streams between parties [1]. BT-enabled SC reduces the workload and ensures traceability, while increasing efficiency, reducing cost, and securing more confidence that the products are genuine and of high quality [2]. Helo and Hao believe it is interesting to note that blockchain is well suited to address the challenges of SCs, and therefore it is vital to adopt BT, with its features of immutability, transparency, and trustworthiness, to provide more visibility and security in the SC [2]. The necessity of carrying this study out is to introduce the cost components and the mathematical cost model of BT-enabled SCS to some companies that may prefer using BT in the SC system instead of their current database systems. Several papers investigate various aspects of SCS in an organization or the implementation of BT in a company; but limited research has been carried out into modeling the BT-enabled SCS cost problems from a mathematical point of view. Therefore, this research helps readers better understand the components and the mathematical model for this system.

The second purpose of this research is to minimize the total costs of the designed mathematical model for the BT-enabled SCS through Evolutionary Computation (EC) algorithms as optimization techniques. To generate the raw data for the model, we revised and designed a mathematical formulation of the Operations Research (OR) model for Pharmaceutical Supply Chain (PSC) and Inventory Management model for a single pharmaceutical company and a single hospital. Using this formulation as a newly designed model, the authors simulated raw data for the BT-enabled SCS model as there is no real data for our BT-enabled SCS model. In the next step, we applied Cuckoo Search (CS), Genetic Algorithm (GA), and Ant Colony Optimization (ACO) algorithms to optimize the main total cost model. This research used a score-based ranking system called Total Ranking Score (TRS) to determine the most reliable predictive algorithms. Our research question is which EC algorithms (among three applied algorithms: ACO/GA/CS) are the best solution(s) for our designed mathematical cost model (BT-enabled SCS), minimizing this total cost model. The outline of this article is as follows: Section 2 reviews the literature on BT-enabled SCS, Private/Public/Hybrid Blockchain, and Evolutionary Computation (ACO/GA/CS). Section 3 contains the Proposed BT-enabled SCS model, and the next section shows Case Study: Healthcare System. The Research Results is in the following section and, finally, we draw a Conclusion and a recommendation for future studies in Section 6.

2. Literature Review

3. BT-enabled SCS

SCS works in a total systems approach to manage the entire flow of information, materials, and services in satisfying customer demand [44,53]. Lambert, Cooper, and Pagh (1998) introduce the comprehensive explanation of SCS as “the integration of key business processes from end-user through original suppliers, which provides product, service, and information that add value for customers and other stakeholders” [3]. Therefore, SC is an organization's network that may have various formats extended from two to more levels, one to more suppliers, or one to more products [44,60]. Li and Wang mention the network structure of SCS for a large-scale production or inventory system. BT performs and shares a distributed database of a public ledger of all transactions, records, or digital events among parties’ participation [4]. The Internet is different from BT as the Internet moves information (not value) as well as copies of things (not original information) [5]. Crosby, et al. also notice BT may play a role as a new engine of growth in the digital economy because we increasingly use the Internet to conduct digital commerce and share our data and life events. To verify ownership of an asset and also trace the transaction history, they assert that BT can register assets to identify by one or more identifiers that are difficult to destroy or replicate. Saberi et al. consider that many SC industries pay special attention to traceability as it is an urgent requirement and a fundamental differentiator (SC industries such as the agri-food sector, pharmaceutical/medical products, and high-value goods). They believe BT is the proper response to this question that whether the current SC information systems can support the information being necessary for the timely origin of services and goods. This, according to them, results in improving SC transparency, security, durability. As the technology accelerates the transfer of data streams between parties, Wang et al. (2019) explain that BT can improve efficiency in SCS as well [6]. Wang et al. continue that BT also can improve inventory management, and ultimately reduce waste and cost by reducing the time products spend in the transit process. Therefore, the benefits of BT for enhancing management of the SC include: a) reducing or eliminating fraud and errors, b) reducing delays from paperwork, c) improving inventory management, d) identifying issues more rapidly, e) minimizing courier costs, and f) increasing consumer and partner trust [7].

2.2 Private/Public/Hybrid Blockchain

Saberi et al. (2018) assert blockchain design can be the network players and the rules to maintain the blockchain. A blockchain is essentially a distributed database of records, or a public ledger of all transactions or digital events that have been executed and shared among participating parties [4]. Each transaction in the public ledger, according to them, is verified by the consensus of a majority of the participants in the system. Once entered, information can never be erased [4]. There are three types of BT based on the technology application: open type (permissionless) or public; closed type (permssioned) or private or corporate; mixed-type or hybrid, an open–type blockchain that uses closed-type platform building technologies to achieve consensus [8].

In a private, unlike in an SC network with known entities working to produce and distribute products, the parties know each other and there is no anonymity [5]. To increases performance and improve scalability in private, the number of distributed nodes added blocks to the chain is small [9]. Toufaily, Zalan, and Dhaou introduce a weakness of private/centralized blockchain that private more exposed to fraud risk because the administration and system design remain focused with one or few. Private blockchain may require different levels of access needs to be crafted for different roles of usage permission [10]. Lai and Chuen state that approval for access permission for participants is necessary meaning that private blockchain networks are for members only. Yang et al. (2020) mention that there is a very high transaction processing rate with very few authorized participants in a private blockchain. Therefore, to get the consensus for the network, a shorter time is used and more transactions can be processed within a second [11]. Private blockchain, according to Yang et al., has very strong data privacy as all nodes should agree by consensus to change data in a private one.

On a public blockchain, companies can easily interact with each other like on the public Internet, as long as privacy, security, scalability, and all other technical challenges identified by interviewees are resolved network [9]. Saberi et al. (2018) suggest that public blockchain uses cryptographic methods to let users enter the network and record their transactions, maintaining trust with many anonymous users. Without any providing forms of identification or asking for permission, public blockchain assumes joining or leaving from the blockchain network is possible for anyone from the public Internet [10]. On the other hand, Yang et al. (2020) highlights the entire node must agree on any change in public blockchain as it records the same information. Therefore, it takes more time to mine

just one block to the blockchain because any change should be recorded in all succeeding blocks [11].
A combination of public and private blockchain is known as Hybrid blockchain or Consortium blockchain which has a semi-decentralized and semiprivate structure and has a controlled user group but works across various organizations [12]. To verify the transaction processes, in the hybrid system, a named leader is assigned instead of a single entity, which is a significant difference of this system [11]. In other words, a hybrid network is a kind of federated blockchain constituted of the low-trust (public blockchain) and the single highly trusted entity model (private blockchain) [11].
The most obvious differences between public and private blockchain can be explained by the type of blockchain adopted – permissioned blockchain: the established organizations (the private and public sectors) and permissionless blockchain in start-ups [9] although they are both decentralized and shared among their users to record all peer-to-peer transactions [11]. Compared to a private or public blockchain, the speed of validation on a public blockchain is likely to be slow [11]. Yang et al. also asserts in a public blockchain, each of the transactions is open for the public to verify. However, to verify and validate transactions, only the trusted parties can be presented in the network in a private blockchain, according to them. Controlling the users in uploading information, according to them, is another issue with a public blockchain. For instance, there is no way to change sensitive information uploaded into the system by anyone in the system [11].

2.3 Evolutionary Computation: ACO/GA/CS
Evolutionary Computation (EC) algorithms are optimization methods and heuristic in nature [13]. EC uses evolutionary principles for automated and parallel problem solving (Drugan, 2019; Jong, 2006). In Heuristic methods, trial and error are used to search for solutions, but it seems EC methods are at a higher level than heuristic methods using information and solutions selection to guide the search process [14]. Three are the main goals for Modern Metaheuristic algorithms to carry out a global search: solving problems faster, solving large problems, and obtaining robust algorithms [16,54]. These algorithms try to find near-optimal solutions as they are a state-of-the-art and efficient strategy [15] and to find a solution that is “good enough” in a computing time that is “small enough” [13]. The obvious efficiency of EC algorithms is that they imitate the best features in nature, in which the fittest selection in biological systems evolves through natural selection over millions of years [16]. There are various EC algorithms for optimization problems including Genetic Algorithms, Simulated Annealing, Ant Colony Optimization, Bat Algorithm, Particle Swarm Optimization, Harmony Search, Firefly Algorithm, Flower Pollination Algorithm, Cuckoo Search, and so forth [14].

2.3.1 Ant Colony Optimization (ACO)
The Ant Colony Optimization (ACO) algorithm came from the collective performance of real-life ant colonies [17,56]. To solve optimization problems, Colorni, Dorigo, Maniezzo, and Trubian (1994) as well as Dorigo and Gambardella (1997) proposed the idea of employing a colony of simple cooperating agents. The simulation approach uses the described behavior of real ant colonies to solve these problems with artificial ants, searching the solution space, simulating real ants, and searching their environment [17]. The next step, according to Nourelfath et al., is to adapt ant colonies with the other combinatorial optimization problems such as the vehicle routing problem, telecommunication networks management, graph coloring, constraint satisfaction, and Hamiltonian graphs [18].

2.3.2 Genetic Algorithm (GA)
GA algorithms, as a powerful tool, solve search and optimization problems based on natural selection principles, natural genetics, and evolution [19]. GA algorithms, as part of Evolutionary optimization techniques, are largely used for engineering problems [20]. They introduce three operators as the procedure of GAs: selection, crossover, and mutation. GA consists of five distinct parts; initialization, fitness assignment, selection, crossover, and mutation [19].
These are five steps to explain the GA process: (a) at each step, the GA process selects individuals from the current population to play the role of parents and produce the children for the next generation; (b) the selection process gives preference to the fittest individuals to let them pass the quality genes to the next generation; (c) a fitness function is used to evaluate the potential solutions and a fitter solution is the one with a better fitness value; (d) this fitness function can be identical to the objective function; (e) a new population of solutions is created using genetic operators [21]. Pourrajabian, Dehghan, and Rahgozar consider that the mutation operator is employed to avoid algorithm converging to local optima, maintaining the genetic diversity.

2.3.3 Cuckoo Search (CS)
Cuckoo Search (CS), as a population-based technique, simulates the parasitic and brooding behavior in some cuckoo species to solve effectively complex optimization problems [22]. Although CS is a quite new nature-inspired EC optimization algorithm, engineering applications extensively use CS as it is highly efficient in solving complex nonlinear problems [23]. CS algorithm has fewer key parameters than other similar algorithms and is easy to implement [22]. Yang (2014) explains that this algorithm is enhanced by the behavior of the so-called Lévy flight of some birds (a kind of swarm intelligence algorithm), rather than by simple isotropic (standard) random walks. CS can explore the search space more efficiently than other algorithms using standard Gaussian processes as Lévy flights have infinite mean and variance [24]. A possible solution in the algorithm is a nest of a cuckoo, and the position of the nest is constantly updated by the combination of the algorithm with Lévy flight, finding a potentially better solution to be a new cuckoo’s nest [22]. According to Afshari, Dehkordi, and Akbari (2016), the main influence for the development of this algorithm is the interesting and different lifestyle as well as egg-laying of a cuckoo. This bird can clearly deceive other birds and make them participate in its own survival [25]. These cuckoos dump some eggs in some nests of host birds: those eggs with more similarity to the host bird’s eggs have a better chance of growing into a mature cuckoo, and the rest are identified and killed by the host bird [26].

3. Proposed BT-enabled SCS model
In this section, a mathematical model is proposed to

minimize the cost of BT-enabled SCS. It needs to consider at least two different cost components to cover the total costs of the system. Therefore, the total cost for BT-enabled SCS (C_{Total}) includes these two main components: Supply Chain System cost (C_{SCS}) and Blockchain Implementation cost ($C_{Blockchain}$):

$$C_{Total} = C_{SCS} + C_{Blockchain} \quad (1)$$

3.1 Cost elements of SCS

Revising the economic model by Belmokaddem and Benatek (2012) as well as the model by Li (2014), there are four components in our formulation of the Supply Chain System cost (C_{SCS}). These components are Production Cost, Procurement Cost, Inventory Cost, and Delivery Cost. Figure 1 illustrates the structure of the SCS in a healthcare system, which is a revised Healthcare SC structure from Mustaffa and Potter's (2009) research.

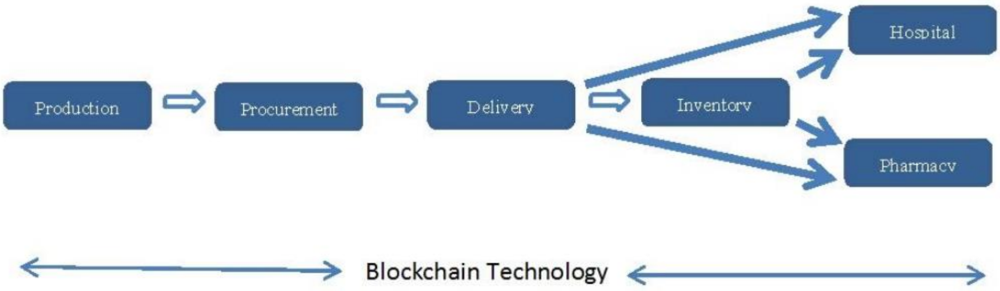

Fig. 1: The SCS structure in a healthcare system.

Therefore, the C_{SCS} can be expressed as follows:

$$C_{SCS} = \sum_{i \in N} [C_{i,Production} q_i + C_{i,Procurement} r_i + C_{i,Inventory} h_i + C_{i,Delivery} f_i] \quad (2)$$

Where $C_{i,Production} q_i$ represents the Production costs ($C_{i,Production}$ is the cost of producing one unit of product i; q_i is the order quantity for the i^{th} product), $C_{i,Procurement} r_i$ is the Procurement costs ($C_{i,Procurement}$ is the supply cost of one unit of i; r_i is the amount of raw material i that must supply per day), $C_{i,Inventory} h_i$ is the Inventory costs ($C_{i,Inventory}$ is the storage cost of product i; h_i is the stock level of product i), $C_{i,Delivery} f_i$ is the Delivery costs ($C_{i,Delivery}$ is the quantity of finished product i distributed per day; f_i is the distribution cost of one unit of i).

3.2 Cost elements of Blockchain Implementation

We then designed the mathematical part for the Blockchain Implementation cost ($C_{Blockchain}$) with two components including Blockchain Transaction cost ($C_{BT\_Transaction}$) and Blockchain Installation cost ($C_{BT\_Installation}$). Identifying the available blockchain platforms is the first step for selecting a blockchain platform to develop a business solution [27]. Various blockchain platforms have been introduced to deploy smart contracts and provide enterprise solutions to issues in numerous industries [27]. Depending on the system requirements of the blockchain application that is developed, a suitable blockchain platform should be selected [27]. In this study, according to the advantages of the Public blockchain in section 2.2, the Public type of Blockchain platform is selected for the SCS as a hosting platform according to our literature section. To select a Blockchain platform, we assumed that the system decides to use the platforms available in the market instead of designing and developing a Blockchain platform.

$$C_{Blockchain} = C_{BT\_Transaction} + C_{BT\_Installation} \quad (3)$$

To measure the Blockchain Transaction cost ($C_{BT\ Transaction}$) within the network, it seems necessary to use an agreed method for transmitting value. There is a transaction fee for a blockchain participant who wants to execute a transaction [28]. To address this issue, Wood (2014) mentions Ethereum is a kind of currency called Ether (ETH) where there is a fee for all programmable computation in Ethereum. The most popular consensus protocol in the public blockchain is Proof-of-Work (PoW), such as in Bitcoin and Ethereum [29]. Two parts determine the cost of the transaction: gasLimit and gasPrice. To calculate the cost of the Ethereum blockchain, Longo et al. state it is necessary to do this calculation based on the gas used by a transaction.

Wood introduces gasLimit as a scalar value equal to the maximum amount of gas that should be used in executing this transaction. Every BT transaction includes a specific amount of gas named gasLimit (purchased from the sender's account balance) in which any unused gas is refunded at the end of the transaction (at the same rate of purchase) to the sender's account [30]. It seems necessary to evaluate gasPrice for every transaction in the Ethereum blockchain if a BT will be used in a real SC context [28]. Wood explains gasPrice (a scalar value) is the number of Wei to be paid for each unit of gas including all computation costs incurred as a result of the execution of this transaction. Longo et al. also point out the Ethereum blockchain's software defines and hard-codes the gasPrice for each operation [30]. A given amount of gas is associated with a transaction after submitting a transaction [28]. Wood (2017) introduces this calculation used by the platform to pay miners: Transaction fee = Total gasUsed × gasPrice paid [62,28].

$$E \times g \times 365 + s \times C_s \quad (4)$$

$E \times g$ is the BT Transaction costs ($C_{BT\_Transaction}$) (E is the amount of Ether as gasUsed per day; g is the of gWei to be paid for gasUsed (per unit of gas/per day). Wei is the unit of ETH typically used to denominate gas prices. We used ETH Gas Station to calculate $E \times g$ to incentivize computation within the network [31,62] (See Figure 2). The authors assumed the amount 65000 as gasUsed and 26 and

333 gWei as gasPrice to calculate E × g cost through the ETH Gas Station website. Based on these ranges, the ETH Gas Station proposes the cost of \$3.36 to \$43.07 per day for E × g.

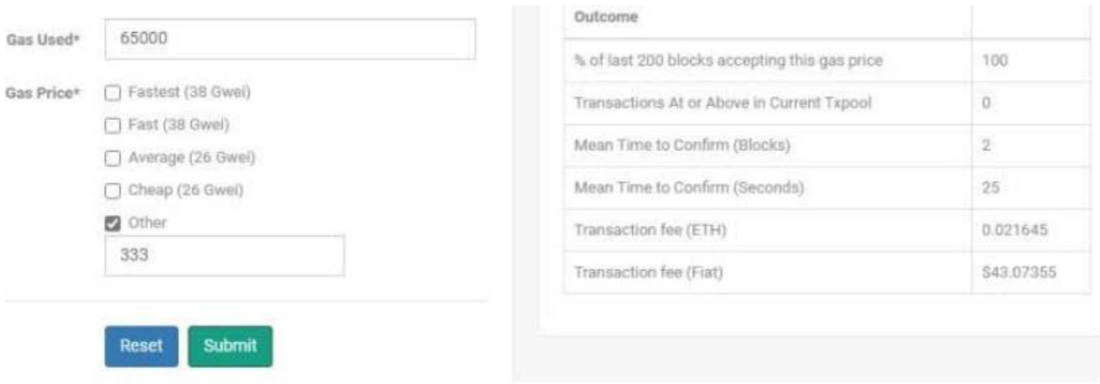

Fig. 2: Transaction cost by ETH Gas Station [31].

Longo et al. (2019) define two costs for BT transaction cost from a simple ether transaction to the execution of a smart contract's function: the gas (the cost of each operation performed on the blockchain) and the storage of data on the blockchain. s × C_s is the storage cost which is a secured cloud-based warehouse to store the actual data off-chain. As IBM Cloud came in with the lowest prices across 67 cloud computing scenarios to beat out Microsoft, Google, and AWS [32], we used this service for the storage cost part. IBM Cloud website proposes a price of \$0.1400 for Public outbound bandwidth (USD/GB) with the range of 0 and 50 TB [33]. The authors, based on the IBM Cloud website, assumed \$1680 (USD/TB) per year (C_s) for Public outbound bandwidth service. s also represents the storage size to store the data ranging from 180 TB to 420 TB per year. Table 1 represents the parameters and constraints (come from variance sources and our imagination) for the BT Transaction costs.

Table 1: Parameters and constraints for the BT Transaction costs.

Parameters	**Explanation**	**Constrains**
Wei	The unit of ETH typically used to denominate gas prices	---
E	The amount of Ether as gasUsed	$\$3.36 \leq E \times g \leq \$43.07$
g	Number of gWei to be paid for gasUsed per day	
s	The data storage size	180 TB/yr $\leq s \leq$ 420 TB/yr
C_s	Cost storage per year (USD/TB)	\$1680

The basic mathematical part of the Blockchain Installation cost ($C_{BT\_Installation}$) in our model comes from the recent research proposed by Gopalakrishnan, Hall, and Behdad (2021). $C_{BT\_Installation}$ is the cost of utilizing BT for SCS, and this cost needs to consider at least four different cost elements including a Fixed cost, Onboarding cost, Maintenance cost, and Monitoring cost.

$$c_{fixed} + (c_{onboarding}\, U + c_{mc} + c_{mo}) \times \text{avg.}(q_i) \qquad (5)$$

where the initial Fixed cost (c_{fixed}) is associated with the utilization of Blockchain; the Onboarding cost (as a function of $c_{onboarding}$) is to train suppliers and clients into active users of a product or service; the Maintenance cost and Monitoring cost are based on the unit Maintenance (c_{mc}) and Monitoring (c_{mo}) cost; q_i expresses the order of products; U is the number of Blockchain users (different types of users) based on consensus protocol in the Blockchain platform. The Maintenance and Monitoring costs occur yearly and contribute to 15–25 percent of the project value [67,64]. The third-party services are used for parts such as mobile apps, admin and web interfaces, and tracking services products [66,64]. Onboarding cost (such as onboarding and training) is any expenses and costs related to integrating new employees into a company to learn and train about BT. We also assumed that SCS uses the platforms available in the market. Table 2 illustrates the parameters and constraints (come from variance sources and our imagination) for the Blockchain Installation cost.

Table 2: Parameters and constraints for the Blockchain Installation cost.

Parameters	**Explanation**	**Constrains**
c_{fixed}	The initial fixed cost per year	$860 \leq c_{fixed} \leq 1160$
$c_{onboarding}$	The Onboarding cost	$\$180 \leq c_{onboarding} \leq \$260$
c_{mc}	The unit Maintenance cost	$\$25 \leq c_{mc} + c_{mo} \leq \$45$
c_{mo}	The unit Monitoring cost	
U	The number of Blockchain users	4
M	Number of products controlled in the Supply Chain Decision variables	122
q_i	Order quantity for the i^{th} product ($i = 1, 2, 3, \ldots, M$)	$50 \leq q_i \leq 100$ (integer)

3.3 Optimization Function of BT-enabled SCS

Updating the Eq. (2) by applying the Blockchain costs in Eq. (4) and Eq. (5), the objective function (6) is to minimize the nonlinear BT-enables SCS costs and can be expressed as follows:

$$C_{Total} = [C_{SCS}] + [C_{Blockchain}]$$
$$C_{Total} = [C_{Production} + C_{Procurement} + C_{Inventory} + C_{Delivery}] + [C_{BT\_Transaction} + C_{BT\_Installation}]$$
$$\min \left(\sum_{i\in N}[\, C_{i,Production} q_i + C_{i,Procurement} r_i + C_{i,Inventory} h_i + C_{i,Delivery} f_i + C_{i,BT\_Transaction} + C_{i,BT\_Installation}]\right) \quad (6)$$

4 Case Study: Healthcare System

4.1 Model of SC in Healthcare System

As the BT-enabled SCS model introduced in this study is newly designed, there is no specific case study matched with its parameters. To generate data for our model, we, therefore, revised the OR model for PSC and Inventory Management for a single pharmaceutical company and a single hospital published by Uthayakumar and Priyan (2013).

A wide range of methodologies that can help healthcare systems including hospitals and can significantly improve their operations is presented in OR [34]. We deeply selected some elements of Model 2, 3, and 7 from Uthayakumar and Priyan's research related to our BT-enabled SCS cost model. As mentioned before, our model contains two different cost components to cover the total costs of the system: Supply Chain System (SCS) cost and Blockchain Implementation cost. Applying simulation technique, this section tries to redesign models for the SCS part of our model (to simulate raw data) which contains four main elements: Production Cost, Procurement Cost, Inventory Cost, and Delivery Cost. Therefore, we present the mathematical formulation in healthcare facilities for each element (using some parts of models in Uthayakumar and Priyan's paper) to generate raw data, evaluating our BT-enabled SCS model, and find the best optimization approach in the result section. PSC can be defined as "the integration of all activities associated with the flow and transformation of drugs from raw materials through to the end-user, as well as the associated information flows, through improved SC relationships to achieve a sustainable competitive advantage" [34,132]. The three main players of PSC are producers, purchasers, and pharmaceutical providers. After receiving the hospital orders of some products (with q_i size), the pharmaceutical company, in each production cycle, starts to produce the product i with the size of nq_i, and then send the order in n lots each of size q_i ($i = 1, 2, 3, \dots, M$) to the hospital.

The following model in Eq. (7) shows the elements of the Production Cost: the Set-up Cost for all finished products in the pharmaceutical company ($\frac{s_i\, d_i}{nq_i}$), the Production Cost for all finished products in the pharmaceutical company ($d_i\, p_{ci}\,(q_i)$), the Screening Cost for all raw materials in the pharmaceutical company ($\frac{s_{ci}\, q_{wi}\, d_i}{nq_i}$), and the Revenue from imperfect raw materials in the pharmaceutical company ($\frac{s_{di}\,\text{avg.}(\beta_i)\, q_{wi}\, d_i}{nq_i}$).

$$\sum_{i=1}^{M}\left[\frac{s_i\, d_i}{nq_i} + d_i\, p_{ci}\,(q_i) + \frac{s_{ci}\, q_{wi}\, d_i}{nq_i} - \frac{s_{di}\,\text{avg.}(\beta_i)\, q_{wi}\, d_i}{nq_i}\right] \quad (7)$$

The following function, in Eq. (8), represents the Procurement Cost including the Cost Order for all M products in the hospital ($\frac{d_i}{q_i}\, a_i$), the Cost Order for all raw materials in the pharmaceutical company ($\frac{a_{wi}\, d_i}{nq_i}$), and the Labor Cost for order handling and receipt for all raw materials in the pharmaceutical company ($\frac{d_i\, q_{wi}\, v_{wi}}{nq_i}$).

$$\sum_{i=1}^{M}\left[\frac{d_i}{q_i}\, a_i + \frac{a_{wi}\, d_i}{nq_i} + \frac{d_i\, q_{wi}\, v_{wi}}{nq_i}\right] \quad (8)$$

The following cost function called Inventory Cost in Eq. (9) for a product i involves: the Holding Cost for all M products in the hospital ($\frac{h_{bi}\, q_i}{2}$), the Holding Cost for all finished products in the pharmaceutical company ($\frac{h_{vi}\, q_i}{2}[n(1 - \frac{d_i}{p_i}) - 1 + \frac{2d_i}{p_i}]$), the Holding Cost for perfect raw materials in the pharmaceutical company ($\frac{d_i\,(1-\text{avg.}(\beta_i))\, q_{wi}\, h_{wi}}{n\, q_i}$), the Holding Cost for imperfect raw materials in the pharmaceutical company ($\frac{h_{wi}\,\text{avg.}(\beta_i)\, q_{wi}\, q_{wi}\, d_i}{r_{si}\, n\, q_i}$), the Safety Stock Cost for all M products in the hospital ($(h_{bi} + p_{hi}\, I_c)\, k_i\, \sigma_i \sqrt{L}$), the Expiry Cost for all M products in the hospital ($d_i\,(z_i\, c_{di}\,(L) + v_i)$), and the Expiry Cost for all finished products in the pharmaceutical company ($q_i\, d_{ci}\, c_{dci}\,[(\frac{d_i}{p_i} + (n-1)) - \frac{nd_i}{2p_i}]$).

$$\sum_{i=1}^{M}\left[\frac{h_{bi}\, q_i}{2} + \frac{h_{vi}\, q_i}{2}\left[n\left(1 - \frac{d_i}{p_i}\right) - 1 + \frac{2d_i}{p_i}\right] + \frac{d_i\,(1-\text{avg.}(\beta_i))\, q_{wi}\, h_{wi}}{n\, q_i} + \frac{h_{wi}\,\text{avg.}(\beta_i)\, q_{wi}\, q_{wi}\, d_i}{r_{si}\, n\, q_i} + (h_{bi} + p_{hi}\, I_c)\, k_i\, \sigma_i \sqrt{L} + d_i\,(z_i\, c_{di}\,(L) + v_i) + q_i\, d_{ci}\, c_{dci}\left[\left(\frac{d_i}{p_i} + (n-1)\right) - \frac{nd_i}{2p_i}\right]\right] \quad (9)$$

The Delivery Cost function (Eq. (10)) for a product i has also these elements: the Transportation and Labor Cost for all M products in the hospital ($\frac{d_i}{q_i}\, F$) and the Transportation Cost for all raw materials in the pharmaceutical company ($\frac{F_w\, d_i}{nq_i}$).

$$\sum_{i=1}^{M}\left[\frac{d_i}{q_i}\, F + \frac{F_w\, d_i}{nq_i}\right] \quad (10)$$

It is assumed that the hospital and the pharmaceutical company, in practice, pay a fixed transportation cost of F_w

and F respectively.
The parameters and constraints (come from variance sources and our imagination) for the Blockchain Installation cost are shown in Table 3.

Table 3. Parameters and constraints for the Blockchain Installation cost.

Parameters	Explanation	Constrains
M	Number of products controlled in the Supply Chain Decision variables	35
q_i	Order quantity for the i^{th} product per year (i = 1, 2, 3, . . . , M)	$50 \le q_i \le 100$ (integer)
d_i	Average demand for the i^{th} product per year	$45 \le d_i \le 75$ (integer)
L	Lead time (days) for all products (days)	12
n	Total number of lots of M products delivered by the pharmaceutical company to the hospital per year	$50 \le n \le 100$ (integer)
z_i	Expiry rate for the i^{th} product at the hospital	$1.04\% \le z_i \le 4.21\%$
h_{bi}	Holding cost per year excluding interest charges for the i^{th} product	$45 \le h_{bi} \le 75$
a_i	Ordering cost per order for the i^{th} product	$65 \le a_i \le 85$
I_c	Interest charge paid per $ in stock to the bank for all products per year	$I_c = 0.03$
p_{hi}	Purchase price per unit for the i^{th} product	$5 \le p_{hi} \le 10$
k_i	The safety factor for a product i	$25 \le k_i \le 35$ (integer)
$\sigma_i\sqrt{L}$	where σ_i is the standard deviation for the demand per year for the i^{th} product	$1\% \le \sigma_i \le 100\%$
F	Fixed transportation cost for all products per delivery per year	4500
h_{vi}	Holding cost for the i^{th} finished product per year	$20 \le h_{vi} \le 40$
s_i	Set-up cost for the i^{th} finished product per year	$12 \le s_i \le 25$
p_i	Production rate for the i^{th} finished produce	$45 \le d_i \le p_i \le 75$
p_{ci}	Production cost for a product i per year	$80 \le p_{ci} \le 120$
v_i	A labor cost for a product i per year	$145 \le v_i \le 195$
d_{ci}	Expiration rate for the i^{th} finished product	$1.2\% \le d_{ci} \le 9.21\%$
c_{dci}	Cost of expiry for the i^{th} finished product	$25 \le c_{dci} \le 55$
c_{di}(L)	Cost of expiry of a linear function of the lead time	$2.6 \le c_{di}(L) \le 5.3$
q_{wi}	Replenishment quantity for the i^{th} raw material for production	$20 \le q_{wi} \le 27$
a_{wi}	Ordering cost for the i^{th} raw material	$15 \le a_{wi} \le 25$
h_{wi}	Holding cost per year for the i^{th} raw material	$10 \le h_{wi} \le 15$
F_w	Fixed transportation cost for all raw materials per year	3500
v_{wi}	Labor cost for order handling and receipt for the i^{th} raw material per year	$16 \le v_{wi} \le 28$
β_i	Defect rate for the i^{th} raw material in an order lot, $\beta_i \in [0, 1]$, a random variable	$0 \le \beta_i \le 1$
s_{ci}	Screening cost per year for the i^{th} raw material	$8 \le s_{ci} \le 13$
s_{di}	Imperfect cost per year for the i^{th} raw material	$11 \le s_{di} \le 15$
r_{si}	Screening rate per year for the i^{th} raw material	$1.04\% \le r_{si} \le 7.2\%$
f_i	Storage space for the i^{th} product	$0.2 \le f_i \le 0.6$
W	Total space available for the M products (m^2)	750

4.2 Data simulation

The authors used Python software to simulate raw data for our main BT-enabled SCS model. Then, the following equations (formulas) were turned into a program in Python: $C_{BT\_Transaction}$ (4), $C_{BT\_Installation}$ (5), $C_{Production}$ (7), $C_{Procurement}$ (8), $C_{Inventory}$ (9), and $C_{Delivery}$ (10). Table 4 illustrates 100 series of the simulated raw data for all six parts of the BT-enabled SCS model, as well as the total cost which is the added values of these parts.

Table 4: The simulated raw data.

No.	$C_{Inventory}$	$C_{Production}$	$C_{Procurement}$	$C_{Delivery}$	$C_{BT\_Installation}$	$C_{BT\_Transaction}$	C_{Total}
1	34205632	16237091.8	2195	126074.7	626075.9	69665.5	51266734.8
2	30357880.1	15845852	2255.8	124662.2	516547	72833.7	46920030.9
3	29933928.7	15531782.3	2190	121330.2	393267.6	80529.6	46063028.4
4	32670868.7	14744994.3	2402.5	135365.9	608133.1	63095	48224859.4
5	28002373	14803589.5	2439.8	135819.9	494836.4	60739.1	43499797.7
6	30977577.9	16652002.2	2392.2	134673.6	443365.7	67517.2	48277528.9
7	31995018.8	14577183.9	2396.7	134074.1	392981.6	64410.6	47166065.7
8	30459533.7	15496064.7	2360.7	130421.2	358494	81618.7	46528493
9	34056545.6	16311475	2309.6	128984.6	651725.2	61472	51212512
10	30625708.4	15581742.8	2360.9	132063.1	532966.4	79484.8	46954326.5
11	31719090.9	15874779.4	2261.3	125837.4	433030.8	74109.6	48229109.5
12	30662660.7	14874716.6	2377.5	133099.1	375081	67564.4	46115499.4
13	31667434.9	14608197.4	2509.6	141334.4	604832.5	58502.5	47082811.4
14	30928928.9	14641305.6	2488.4	134759.1	348223.8	71313.9	46127019.8
15	27843036.9	16763910.4	2243.8	125604.9	671907	82445.9	45489148.9
16	28107666.6	15141932.4	2323.6	130532.1	499639.6	80121.3	43962215.6
17	31127976.4	14797422.1	2253.9	127416	476840.2	71717.2	46603625.8
18	26396159	16647587.5	2328.9	129259	654216.4	63852.6	43893403.5
19	29239131.8	16219659.8	2326.7	127447.6	572750.9	81698.2	46243015

20	32097476.7	15003667	2298.5	129400.2	627322.8	77526.2	47937691.5
21	27388614	15111947.7	2462.7	139478	707911.8	75526.5	43425940.5
22	25865617.3	14731218.5	2567.8	142081.8	474579.2	57752	41273816.7
23	28129379.5	15075683.3	2493.2	135721.1	670929.8	66633.7	44080840.7
24	30489457.9	16091938.2	2423.6	136101.7	690577.6	62644.2	47473143.2
25	26933370.1	13747712.9	2490.2	136637.8	645330.4	54824	41520365.3
26	28911628.1	15040243.1	2435.9	135176.7	474735.2	67537.3	44631756.3
27	25463762.2	15771536.8	2459.2	136056.9	586608	62841	42023264.1
28	32441669.1	15618856.5	2234.6	126544.9	478327.2	61344.1	48728976.3
29	33566323.1	15095432.1	2323.7	129341.9	316771.4	69333.2	49179525.4
30	33934607.1	16534362.4	2246.1	125258.2	387109.8	68895.3	51052478.9
31	28209557.1	14805188.1	2637.2	147349.7	479269.8	63357.8	43707359.7
32	29705452.8	14339504.7	2206.7	122619.2	558445.5	76121.4	44804350.3
33	36580291.6	16181546.1	2392.6	133699.5	660288.8	77088.9	53635307.4
34	28112507.9	15358455.9	2460.4	138993	710751.4	61218.5	44384387.1
35	30621108.3	15102483.5	2484.4	139704	353043.2	55889.1	46274712.6
36	26250290.9	14342230.6	2495.9	137424.9	594539.8	69308.6	41396290.7
37	30451447	14811299.7	2486.4	136616.3	499045.9	67946.7	45968842
38	30102521.8	16119401.4	2213.7	122253.8	466893.3	79908.6	46893192.7
39	28212776.4	15072332.9	2367.4	134776.6	420176.5	72916	43915345.7
40	29756054	15209552.4	2268.4	128393.7	352996.8	63421.5	45512686.8
41	35511865.4	17023416.7	2220.3	123564.8	586474.6	84587	53332128.8
42	32742466.6	15502586.7	2346.5	131198.5	698460.6	73913	49150971.9
43	28041675	15520558	2379.5	131017.8	686771.6	73667	44456068.8
44	27868224.9	14538944.1	2361.8	132353	473121.9	62478.4	43077484.1
45	25138267.1	14498531.8	2418.8	133340.5	429997.7	73025.2	40275581
46	33903273.2	14843685.1	2190.1	122936.1	657740.7	75601	49605426.4
47	32658182.7	16528934.5	2435.9	135122.7	455216.6	75259.4	49855151.8
48	29316115.2	14479719.4	2355.1	129284.7	330160	76900.3	44334534.7
49	29638526.6	15003849.6	2498.6	139762.5	448294.2	68760.5	45301692
50	39431225.1	15607043.6	2346.5	130057.5	541215.2	72307.5	55784195.4
51	31770224.5	15876658.5	2416	133934.1	704207.6	75721.5	48563162.3
52	30196007.2	14726152.6	2459.3	136025.2	462498	64719.3	45587861.6
53	30530882.3	14846816.7	2372.6	131849.1	323393.5	69171.6	45904485.8
54	31211679.7	15003477.7	2425.1	133985	529138.2	68095.1	46948800.9
55	31269236.8	15863408.1	2296.8	127144.2	700439.8	63846.3	48026372.1
56	32604149.8	15641553.6	2324.7	128006.1	325478.6	67069.7	48768582.5
57	32234013.6	16102422.6	2365.3	128372.1	574306.4	80467.7	49121947.7
58	29129877.2	15961793.5	2422.6	134983.7	321547	73399.6	45624023.5
59	28221603.6	15457885.9	2376.6	132111.4	347047.6	77520.4	44238545.5
60	27212213.3	15724100.6	2439.3	135402	566283.1	72732.1	43713170.3
61	29870533.5	15971459.4	2256.8	128006.4	620724.3	66427.4	46659407.8
62	26672049.5	16131430.2	2385.6	133646.6	664295.8	81136.3	43684944
63	33021546.7	17175247.7	2233.3	124059.1	380208.2	84083	50787378
64	28750663.5	17275414.5	2251.3	127511.4	363001.8	71930.4	46590772.9
65	27844381.4	14302035.9	2684.4	145798.4	557882.4	53156.5	42905939
66	30480853.3	14425754	2413.9	133978.9	661035.4	74608	45778643.5
67	26493526.9	14552405.1	2432.6	134991.1	554266.2	71181.3	41808803.3
68	31404442.3	15193556.7	2171.2	122453	565541.4	72736.7	47360901.2
69	35103962	14753769	2491.3	138429.4	603369.5	61108.5	50663129.7
70	29964223	15373950.7	2363.5	131837.7	466420.8	78620.6	46017416.3
71	31702820.7	15606633.1	2386.4	132534.8	630582.3	58976.3	48133933.6
72	33677043.6	14660117.7	2309.2	128910.4	485745.3	76091.7	49030217.9
73	32997265.9	16121673.2	2379.8	129836.5	573036.2	63660.9	49887852.5
74	34291083.4	16491803.9	2301.4	128558.7	458485	68307.7	51440540.1
75	30380474.3	15636928.5	2334.8	131246.8	535224.2	74939.6	46761148.1
76	28025073.9	16577959.8	2209.8	124666.6	641002.8	80443.3	45451356.2
77	34019579.6	15299169.4	2384.9	130724.3	534574.8	66855.1	50053288.1
78	30057766	15109794.1	2550.2	139937.9	529526.8	57744.9	45897319.9
79	26378002.7	15056295.6	2423.8	132090	448880.2	78585	42096277.2
80	32608045.9	15274089.5	2393.2	131587.9	669156	66599.4	48751871.8
81	32892334.8	14772104.2	2341.7	130339.3	699368.4	73155.8	48569644.2
82	28619045.2	14930728.6	2304.5	128353.1	398739	66638.8	44145809.1
83	34773199.3	15403756.1	2340.9	131420.1	569824.2	63052	50943592.7
84	32404360.5	14630619.5	2345.6	132779.6	351720.9	66038	47587864.1
85	32592666.7	15651688.3	2416.2	135802.4	667067.8	78175	49127816.5
86	35076072.9	16434465.6	2350	131117.7	497422	62368.1	52203796.3
87	34654944.2	15344798.7	2363.3	128813.5	569373.3	65059.6	50765352.6

88	31828350.6	15289168	2461.8	135044	620357	58050.3	47933431.8
89	35330852.7	15157112.2	2192.1	123594	526796.6	78525.9	51219073.5
90	27668419.9	15804944.6	2464.4	134198.8	359864.8	59100.5	44028992.9
91	30694869.4	14799528.6	2303	129747.7	400770.4	69272.1	46096491.4
92	25309801.9	14252068.8	2363.8	130939.6	410981.2	64948.3	40171103.4
93	31046568.6	16204955.4	2353.5	130186.5	586550.6	69458	48040072.5
94	29334682.1	15410773.8	2507	141074.3	622363.2	55116.5	45566516.8
95	25397027.8	16246241.5	2475.4	136051.2	546832.5	81396.5	42410024.8
96	31220403.8	15553609.4	2313.5	130399.1	342061.6	58052	47306839.5
97	31589283.6	15509291	2349.1	130248.6	481801	80611.2	47793584.6
98	30067878.8	15531262.5	2251.3	125644	354213.2	61303.3	46142553.2
99	32174028.5	15879305.6	2184.2	123438.8	501891.6	78208.3	48759057
100	29001793.5	16148213	2283.9	129633.7	426225.2	64571.8	45772721.3

5 Results

In this section, we used three EC algorithms (CS, GA, and ACO) to find the minimum total cost for our BT-enabled SCS model, using the simulated data, as our case study in section 3.5. Therefore, to optimize the parameters of the model, Eq. (11), which is the revised version of Eq. (6), calculated total costs for all 100 series of simulated data (Table 4) through three mentioned EC algorithms coded in Matlab. The objective function of EC algorithms is Eq. (11) which should be minimized:

$$\min \left(\sum_{i\in N}[\, C_{i,Production}\mathrm{Q} + C_{i,Procurement}\mathrm{R} + C_{i,Inventory}\mathrm{H} + C_{i,Delivery}\mathrm{F} + \mathrm{C}_{i,BT\_Transaction} + \mathrm{C}_{i,BT\_Installation}]\right) \quad (11)$$

$$0 \leq i \leq 100 \quad (12)$$

$$\mathrm{R} \leq \mathrm{F} \quad (13)$$

$$\mathrm{Q} \leq \mathrm{F} \quad (14)$$

$$\mathrm{F} + \mathrm{R} \leq \mathrm{H} \quad (15)$$

$$\mathrm{Q} + \mathrm{R} \leq \mathrm{H} \quad (16)$$

Where $C_{i,Production}$Q represents the Production costs in the pharmaceutical company ($C_{i,Production}$ is the cost of producing all products in the i^{th} series of data; Q is the order quantity of a hospital for each series of data); $C_{i,Procurement}$R is the Procurement costs ($C_{i,Procurement}$ is the cost order for all products in the hospital in the i^{th} series of data; R is the amount of all products in the hospital for each series of data); $C_{i,Inventory}$H is the Inventory costs in both hospital and pharmaceutical companies ($C_{i,Inventory}$ is the storage cost of all products in the i^{th} series of data; H is the stock level of each series of data); $C_{i,Delivery}$F is the Delivery costs to both hospital and pharmaceutical companies ($C_{i,Delivery}$ is the distribution cost to both hospital and pharmaceutical companies in the i^{th} series of data; F is the quantity of all finished products for each series of data); and BT cost ($\mathrm{C}_{i,BT\_Transaction}$) and Blockchain Installation cost ($\mathrm{C}_{i,BT\_Installation}$) are the costs for the i^{th} series of data. The authors, based on constraints, assumed the following parameters as constants with these values before running the selected algorithms: R = 30; F = 35; Q = 25; H = 75.

The performance of the applied algorithms is evaluated by some well-known accuracy criteria, namely the Mean Square Error (MSE), Root Mean Square Error (RMSE), R^2, and Area Under the ROC Curve (AUC-ROC or simply AUROC). The MSE was defined as the objective function to measure the performance error after each try. A code written by Matlab was used for the optimization procedure, and the maximum number of iterations is set to 2000 for all three algorithms. The reason behind evaluating various criteria is that the problem with MSE and RMSE, not even getting deep into the details, stems from the fact that they are just based on an error assessment, while the models should be treated holistically based on their all capabilities [35]. To compare the declining trend of the error, the convergence curves of training error of all three algorithms (CS, GA, and ACO) are presented in Figure 3. The convergence curve of both GA and ACO remained steady on the MSE of around 0.09 after iteration 1000. However, CS shows an MSE of around 0.075 after iteration 1000, which has the minimum training error and better results compared to the other algorithms even in the low number of iteration. The baseline, in this figure, also illustrates the minimum training error as an indicator for comparison.

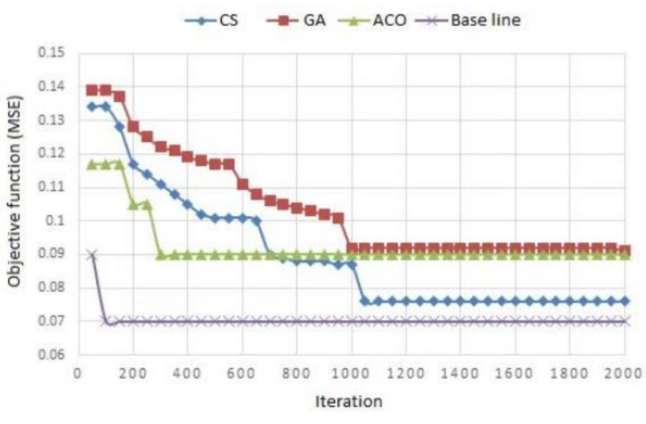

Fig. 3: The convergence curves of training error for CS, GA, and ACO.

Figure 4 illustrates the cost minimization results for all three algorithms. As depicted in this figure, there is a significant difference in the convergence rates between ACO and the rest functions. Algorithms CS and GA converge similarly, slightly cheaper than ACO. Now it is seen that ACO has not been able to find the global minimum in 2000 iterations, but CS has reached a global minimum at the 800th iteration.

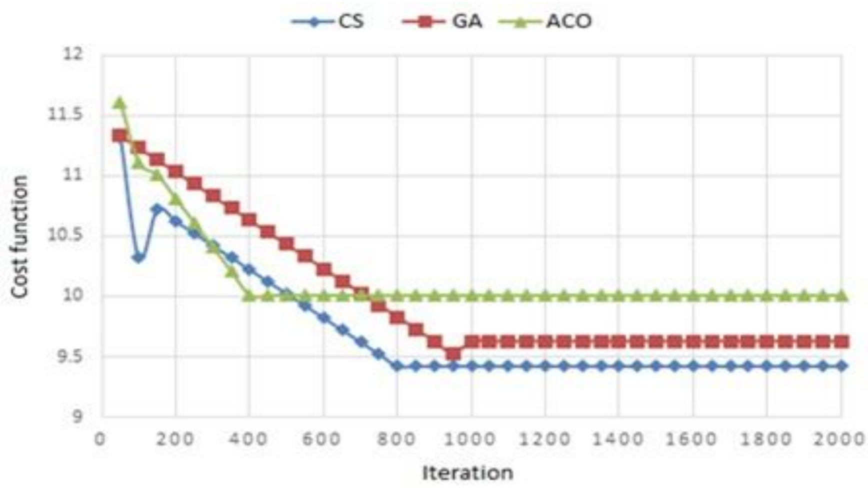

Fig. 4: Comparison of convergence curves for the cost function of CS, GA, and ACO.

Figure 5 shows the comparison of running time results (seconds) over 2000 iterations for CS, GA, and ACO algorithms. As it can be seen in the figure, CS has been converged with a high speed and in the lower number of iteration, less than 900, can attain a better solution compared to others. ACO and GA also take longer to find a solution.

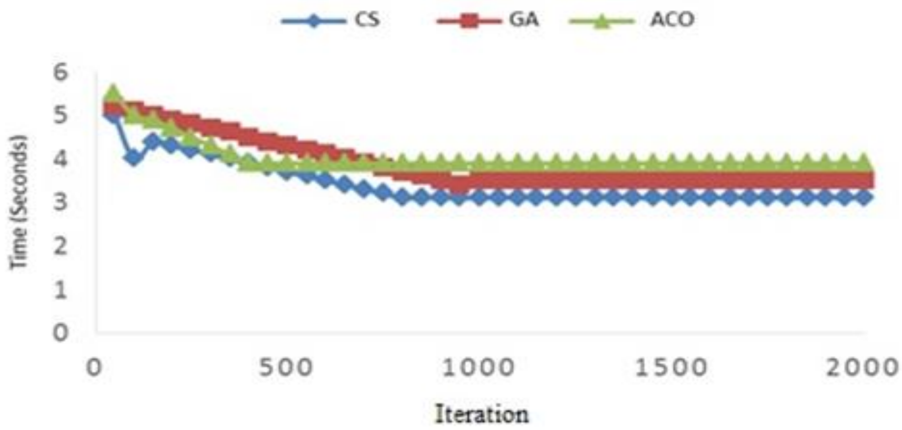

Fig. 5: Running time comparison (seconds) of CS, GA, and ACO.

The performance of the applied algorithms is evaluated by some criteria, namely MSE, RMSE, Error Mean, and Error St.D. in Figure 6. The simulated data were randomly examined via 70:30 partitioned data sets where a testing dataset was 70% for training the models and the remaining 30% was used for the validation purpose.

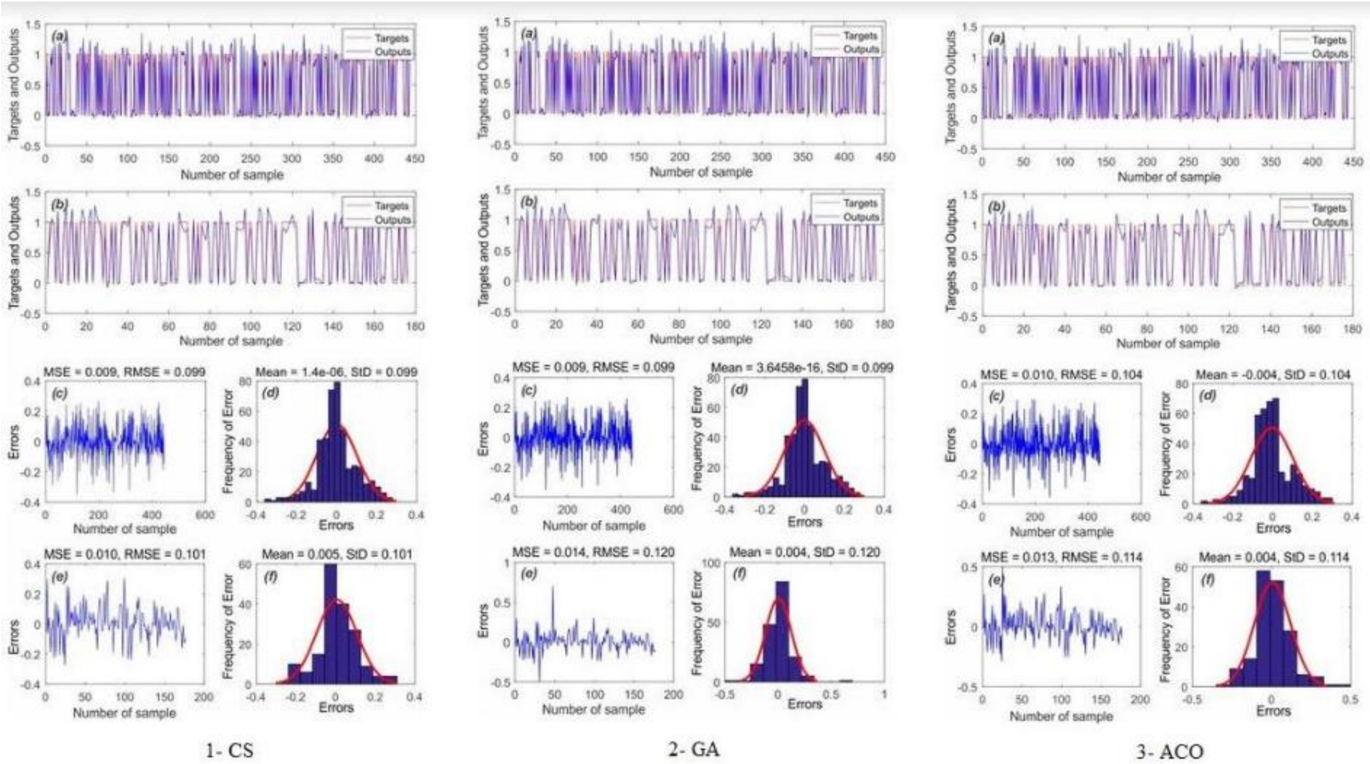

Fig. 6: The results were obtained for 1- CS, (b) 2- GA, and 3- ACO in which (a, c, d) and (b, e, f) were allocated to training and testing phases respectively.

The combination of an ANFIS model and a NARX structure called the ANFIS–NARX method provide a powerful system to create an accurate and transparent identification method, which is the combination of universal approximation capability, transparency of fuzzy inference system, and training ability of neural networks with an adaptive and predictive potential of NARX structure [36]. They assert that the main reason for ANFIS–NARX selection is its interpretability, transparency, and readability as well as better estimation accuracy that are important characteristics playing a significant role in the performance of the system and its superiority. We, therefore, used a combination of ANFIS-NARX with three EC algorithms called CS-ANFIS–NARX, GA-ANFIS–NARX, and ACO-ANFIS–NARX to compare the accuracy. After training ANFIS–NARX by EC algorithms, the Receiver Operating Characteristic (ROC) curves for testing predictions of the three algorithms were plotted in Figure 7. To assess the performance of algorithms, the results are analyzed, and the prediction accuracy of the employed ensembles is evaluated by ROC. The ROC curve is a common method to determine the accuracy of a diagnostic test, and it is considered as a graphical representation of the trade-off between the false-negative (X-axis) and false positive (Y-axis) rates for every possible cut-off value [35]. The Area Under the ROC Curve (AUC-ROC or simply AUROC) represents the prediction value of an algorithm (and the accuracy of the prediction) characterized by its ability to compare quantitatively between various ROC curves and estimate the true positive and negative events. This value summarizes the corresponding ROC curve into a single value between 0 and 1. According to these figures, all of the obtained ROCs in the testing phase show a high accuracy (>80%) for the EC-ANFIS-NARX. In detail, the highest accuracy, among three algorithms, for predicting (83.9 % accuracy) was obtained by the ACO-ANFIS-NARX, followed by the CS-ANFIS–NARX 83.3 %), and the GA-ANFIS-NARX (81.9 %). Part (d), as the Total Average for all algorithms, illustrates the accuracy which is higher than the accuracy of the three algorithms to produce the reasonable global minimum outputs for the BT-enabled SCS cost model. The parameter sets used in CS, GA, and ACO are also compared in Table 5.

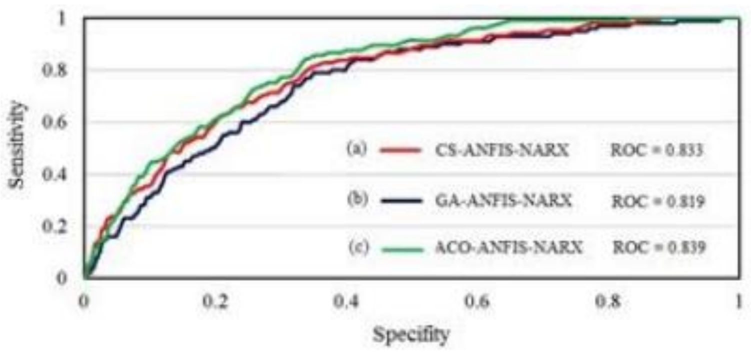

Fig. 7: The ROC curves were plotted for the testing dataset and obtained from the ensembles of (a) CS-ANFIS-NARX, (b) GA-ANFIS-NARX, and (c) ACO-ANFIS-NARX.

The results of the optimization for three algorithms are summarized in Table 5. There are two approaches to train and test the data set and then to evaluate the used model through CS, GA, and ACO algorithms. In both Ensemble and Network approaches, the results illustrate the ranking score in both training and testing phases for ROC are similar, showing a good accuracy of the used model. ACO has the better accuracy (ROC) in both approaches and phases, and GA stands in the third level. Therefore, all three algorithms have an acceptable accuracy obtained from ROC to perform consistently in both approaches/phases and reach the global minimum for the BT-enabled SCS cost model. MSE in both approaches and phases indicates the minimum amount in CS except in the testing phase of the Network approach where it has the maximum amount. The table denotes that while the CS in both phases of the Ensemble approached reached the lowest RMSE, ACO kept decreasing the RMSE in Network approach in both phases. Having a look at MSEs and RMSEs values in the training phase indicates that CS is genuinely doing better than other approaches in learning the pattern. All obtained results from MSEs and RMSEs show a good capability of the used models for predicting the unseen costs. To determine the most reliable predictive algorithms, a score-based ranking system called Total Ranking Score (TRS) is finally used [37]. In this procedure, each model receives a score based on the calculated MSE, RMSE, and ROC in both approaches and phases. Eventually, the ranking position of each model is allocated to the summation of all acquired scores states [37]. In TRS, the lowest MSE and RMSE receive the highest scores and the highest ROC has the highest score (and vice versa). The overall results of this study show that both CS and ACO algorithms have performed better than the compared algorithm and achieved the first position in terms of all criteria with a TRS of 27, followed by GA with a TRS of 18.

Table 5: The developed ranking system based on MSE, RMSE, and ROC criteria.

Algorithms		Ensemble medels						Network results						TRS	Rank
		Training phase			Testing phase			Training phase			Testing phase				
		MSE	RMSE	ROC	MSE	RMSE	ROC	MSE	RMSE	ROC	MSE	RMSE	ROC		
CS		0.086	0.294	0.833	0.08	0.284	0.833	0.075	0.275	0.835	0.069	0.277	0.830		
GA		0.088	0.297	0.818	0.081	0.285	0.819	0.077	0.278	0.819	0.065	0.276	0.818		
ACO		0.087	0.295	0.841	0.084	0.29	0.839	0.078	0.269	0.840	0.066	0.275	0.839		
Ranking score	CS	3	3	2	3	3	2	3	2	2	1	1	2	27	1
	GA	1	1	1	2	2	1	2	1	1	3	2	1	18	2
	ACO	2	2	3	1	1	3	1	3	3	2	3	3	27	1

6 Conclusion

This paper introduces the cost components of BT-enabled SCS including the Production costs (in the pharmaceutical company), Procurement costs, Inventory costs (in both hospital and pharmaceutical company), Delivery costs (to both hospital and pharmaceutical company), Blockchain Transaction cost (gasUsed and gasPrice), and Blockchain Installation cost (Fixed cost, Onboarding cost, Maintenance cost, and Monitoring cost). To evaluate the total costs of the system, these components are useful for companies and organizations that tend to use Public BT as the main database in their SC system. Another advantage of this paper is to model the mathematical formulation for the BT-enabled SCS based on the mentioned components. The simulated raw data for the main BT-enabled SCS model is another output for this research, which comes from the designed mathematical formulation in healthcare facilities (the OR model for PSC and Inventory Management for a single pharmaceutical company and a single hospital). This mathematical formulation helps other studies that have a limitation of finding real data generate raw data in a healthcare field for their research. According to Yang (2014), there are many optimization algorithms in the literature and no single algorithm is suitable for all problems.

This paper found out that both CS and ACO algorithms fulfill the BT-enabled SCS cost model with the higher TRS (including MES, RMSE, and ROC) than the GA. Compared with other metaheuristic algorithms, CS seems to be more generic and robust for some optimization problems [16]. The results also show GA, based on TRS, stands in the second step for this case. While the ROC of ACO is higher than others, CS comes in the second level, followed by GA. The more interesting finding is that all three applied algorithms produce reasonable global minimum outputs for the BT-enabled SCS cost model. This means that our cost model can fulfill all three mentioned algorithms as the accuracy of the three algorithms to produce the reasonable global minimum outputs for the BT-enabled SCS cost model seems acceptable. According to reaching the reasonable global minimum outputs for the BT-enabled SCS cost model by the three algorithms, we also find out that the designed mathematical formulation in healthcare facilities is able to give us the reliable simulated dataset as it ends up with the high ROCs and low MESs/RMSEs in the main model.

The authors suggest examining this mathematical model with a private or hybrid BT system for future research. This results in changing some parts and components of the Blockchain Implementation cost (these components in our case are the Blockchain Transaction cost and the Blockchain Installation cost). In this regard, the future study will be able to compare the costs of this study with the new one to show which direction has the lowest cost. One remaining question is to examine this model using our simulated data with some other metaheuristics algorithms to identify and compare it with our three results of CS, ACO, and GA. Therefore, readership can understand which algorithm is more suitable for the mentioned model. Last but not least, it is needed to investigate the performance of the BT-enabled SCS cost model in real problems after proving in test cost functions.

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